Ecological Indicators 95 (2018) 805–814

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Original Articles

An assessment of the impacts of climate extremes on the vegetation in Mongolian Plateau: Using a scenarios-based analysis to support regional adaptation and mitigation options

Chunlan Li[a,b,c,d], Walter Leal Filho[c,d,*], Jun Wang[a,b,*], Jie Yin[a,b], Mariia Fedoruk[c,d,e], Gang Bao[f,g], Yuhai Bao[f,g], Shan Yin[f,g], Shan Yu[f,g], Richa Hu[f]

[a] School of Geographical Sciences East China Normal University, Shanghai 200241, China
[b] Key Laboratory of Geographic Information Science of Ministry of Education, East China Normal University, Shanghai 200241, China
[c] Hamburg University of Applied Sciences, Research and Transfer Centre "Sustainable Development and Climate Change Management", Ulmenliet 20, D-21033 Hamburg, Germany
[d] School of Science and the Environment, Manchester Metropolitan University, UK
[e] Institute for Ecological Economics and Management Ukrainian National Forestry University, 79057, Ukraine
[f] College of Geographical Sciences, Inner Mongolia Normal University, Huhhot 010022, China
[g] Key Laboratory of Remote Sensing and Geographic Information System, Inner Mongolia, Huhhot 010022, China

ARTICLE INFO

Keywords:
Normalized difference vegetation index (NDVI)
Climate extremes
Greenhouse gas (GHG) emission
Scenarios-based analysis
Adaptation and mitigation options
Mongolian Plateau (MP)

ABSTRACT

Climate change is known to have an impact on the vegetation and on the well-being of ecosystems. Whereas there is a limited number of studies which have assessed historical vegetation changes in the Mongolian Plateau (MP), there are even fewer considering future changes. This paper therefore fills a gap in the literature, by investigating such changes in temporal and spatial scales, and by assessing their effects (1982–2100). The methods used in the study mainly included Pearson correlation and Mann-Kendall test. Results showed that climate extremes in MP, significantly influence vegetation growth. In addition, vegetation trends in MP, vary according to different scenarios. Potentially vulnerable areas of grassland and forest in the future are pointed out. Among the adaptation options available, better management of farmland and water resources should be pursued, and planting of vegetation types should be considered separately. Improvement of the barren area in MP requires international cooperation between Mongolia and China and it is necessary to integrate adaptation options into relevant policies. For mitigation, the projection indicates the emission under Scenario A1B is better for grass growth in MP and great attention should be paid to the greenhouse gas (GHG) emissions from grassland systems in detail, apart from the high quality and low GHG emission animal species, the types of intake grass also need to be seriously considered. In addition, management of sheepfolds in MP is also an important way to reduce GHG emissions. The results from this study will provide useful information about appropriate adaptation and mitigation strategies which may influence vegetation growth in MP.

1. Introduction

A climate extreme (extreme weather or climate event) means the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of a given variable. For simplicity, both extreme weather events and extreme climate events are referred to collectively as climate extremes (Field et al., 2012). However, the description of climate extreme is still complex, even if in a statistical sense, there is no extreme, it can still lead to extreme conditions or impacts (Nicholls et al., 2012). An Expert Team on Climate Change Detection and Indices (ETCCDI) of the World Meteorological Organization Working Group has attempted to facilitate the analysis of such climate extremes by defining a set of extreme climate indices that provide a comprehensive overview of

* Corresponding authors at: School of Science and the Environment, Manchester Metropolitan University, UK & Hamburg University of Applied Sciences, Research and Transfer Centre "Sustainable Development and Climate Change Management", Ulmenliet 20, D-21033 Hamburg, Germany (W. Leal Filho). School of Geographical Sciences East China Normal University, Shanghai 200241, China; Key Laboratory of Geographic Information Science of Ministry of Education, East China Normal University, Shanghai 200241, China (J. Wang).
E-mail addresses: walter.leal2@haw-hamburg.de (W.L. Filho), jwang@geo.ecnu.edu.cn (J. Wang), baogang@imnu.edu.cn (G. Bao), baoyuhai@imnu.edu.cn (Y. Bao), yinshan@imnu.edu.cn (S. Yin), huricha@imnu.edu.cn (R. Hu).

https://doi.org/10.1016/j.ecolind.2018.08.031
Received 20 February 2018; Received in revised form 11 August 2018; Accepted 14 August 2018
Available online 23 August 2018
1470-160X/ © 2018 Elsevier Ltd. All rights reserved.

temperature and precipitation statistics focusing particularly on extreme aspects (Sillmann et al., 2013a). Until now, these sets of extreme climate indices have been widely used by many scholars. For instance, the indices are well used not only in global studies (Sillmann et al., 2013a,b), but also in regional studies (Xu et al., 2015; Wu et al., 2017; Arefi et al., 2017).

Some changes in climate extremes observed in the late 20th century are projected to continue (Kharin et al., 2013) in particular:

a) temperature extremes keeping substantial warming (Seneviratne et al., 2012),
b) precipitation with high frequency and proportion increasing by the end of the 21st century over many areas of the globe (Nicholls et al., 2012).

In addition, extreme events are expected to increase not only in their frequency but also in their magnitude (Ferńandez-Gimenez et al., 2012). The effects of climate extremes are widely spread in semiarid biomes, which cover 40–50% of the terrestrial surface and where 40% of the world population lives (Reynolds et al., 2007). To date, only a few studies have been focused on the impacts of extreme winters unique to the Mongolian Plateau (Hoover et al., 2016), where one of the largest remaining grassland ecosystem is located (Angerer et al., 2008). While compared with other land use types, grassland is most sensitive to climate extremes (Zhang et al., 2017).

The grassland ecosystems in Mongolian Plateau (MP), mainly including Mongolia (M) and Inner Mongolia (M) of China, are very special. It not only provides abundant natural resources for the regional economic development but also safeguards the environment of Asia as it acts as an ecological protective screen (Dan et al., 2013). However, grassland degradation has become one of the most serious environmental problems and is posing a threat to sustainable development of this area (Miao et al., 2015). This is because the livelihoods in MP are primarily based on livestock and grassland resources (Miao et al., 2015). Researchers have found rangelands in IM have been steadily deteriorating at a rate of approximately 2% of the land area annually (Angerer et al., 2008), and account for 59% of the total grassland area in IM compared with its value in the 1950s (He et al., 2015). While in M, 70–80% of pastures suffered from degradation of varying intensity (Tian et al., 2014), and rangeland degradation near settlements, roads, and water points have also been observed (Angerer et al., 2008). For grassland changes, effects contributed by climate extremes are also huge and cannot be ignored (Mu et al., 2013). Thus, detecting and understanding how future climate extremes potentially affect vegetation change in MP and mitigation and adaptation of these climate extremes, are urgent and this knowledge may guide measures which also bring benefit for indigenous pastoralists, who rely on stock farming.

Knowledge regarding vegetation responses in MP to external impacts is at present still incomplete, especially those influenced by climate extremes. Hitherto, there is a paucity of studies considering the combination of the climate extremes depending on the amount and quality of relevant observational data. Based on this, the specific questions tackled by this paper are: (1) how has vegetation responded to climate extremes in the past, especially throughout the last decades (1982–2014), across MP? and (2) were there any significant differences in the vegetation responses between the two political units, IM and M? (3) The answers to these questions may assist efforts towards adaptation and mitigation to climate extremes.

2. Study area

The investigated site consisted of parts of Mongolia (M) in the northwest and Inner Mongolia, China (IM) in the southeast. The Mongolian Plateau (MP) lies in between latitudes 37°22′ N ~ 53°23′ N and longitudes 87°43′ E ~ 126°04′ E (Fig. 1). It covers a total area of 2.75 billion km^2, with an average elevation of 1600 m above sea level.

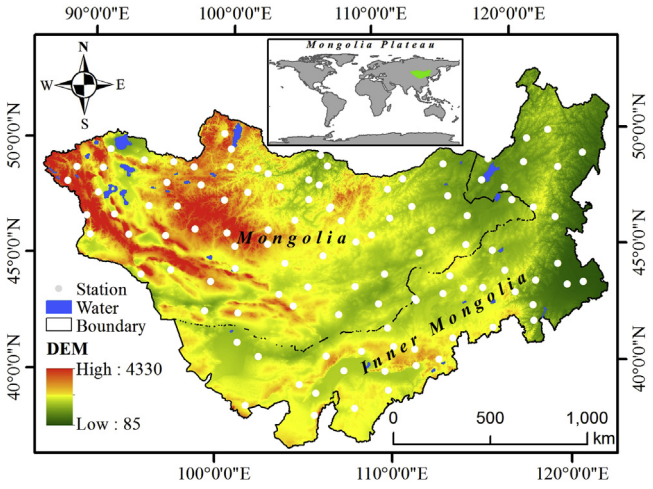

Fig. 1. Location of Mongolian Plateau (MP).

In this area, low mountains are located in the east while high mountains are distributed in the west, and the Yinshan mountain ranges to the south, with the Sayan and Hentiy mountain range to the north. The average annual temperature varies approximately −26 to 17 °C while the annual average precipitation in most regions is < 200 mm, although it may reach 400 mm or higher in the eastern, northeastern, or northern mountainous areas (Zhang et al., 2009). The unique location determines its special distribution of vegetation. There are three biomes in MP, including forest (northern and eastern parts), grassland (middle) and Gobi Desert (west). Most of the regions are covered by desert, vegetation and sparse grasslands. Livestock and grassland resources are the primary livelihoods (Miao et al., 2015), MP experiences a typical continental climate with extreme cold in the winter and heat in the summer (Zhang et al., 2009) and has suffered some extreme events, such as frequent drought and heavy snowfall (Rao et al., 2015).

3. Data and methods

3.1. Data

3.1.1. Observation data

The recorded daily maximum and minimum temperature, and precipitation data for the forty-three and sixty-eight meteorological monitoring stations in IM and M, respectively during 1982–2014, were used in this study. The data in IM were obtained from the Climate Data Center (CDC) of the National Meteorological Center of the China Meteorological Administration (CMA), while the data in M were obtained from the Information and Research Institute of Meteorology, Hydrology and Environment, in Mongolia. Before obtaining the station-based extreme climate indices, daily data, quality control and homogeneity assessment in the 111 meteorological stations were processed by RClimDex Software Version 1.1 (available from http://etccdi.pacificclimate.org/authenticated_downloads/RClimDex/rclimdex1.1_131115.r) and RHtest V4 software (Available online at http://etccdi.pacificclimate.org/software.shtml), respectively (Li et al., 2018a).

Taking daily maximum and minimum temperatures, and precipitation as inputs, through the RClimDex 1.1, twenty-six core station-based observations of extreme climate indices (16-temperature based and 10-precipitation based) were calculated (as the output data), and their details can be seen in Table 1.

3.1.2. Model data

Land-use and land-cover change data at a 1 km resolution for 2010 to 2100 based on Human-Environment interactions (Li et al., 2017), was used in this study to represent the simulation of vegetation change. This data was simulated by a new model proposed by Liu et al. (2017),

Table 1
Temperature and precipitation indices selected for this study with indicator names, definitions, units.

ID	Indicator name	Definitions	Units
Temperature Intensity			
TXx	Max Tmax	Monthly maximum value of daily maximum temperature	℃
TNx	Max Tmin	Monthly maximum value of daily minimum temperature	℃
TXn	Min Tmax	Monthly minimum value of daily maximum temperature	℃
TNn	Min Tmin	Monthly minimum value of daily minimum temperature	℃
DTR	Diurnal temperature range	Monthly mean value of difference between Tx and Tn	℃
Temperature Duration			
GSL	Growing season Length	Annual (1st Jan to 31st Dec in NH, 1st July to 30th June in SH) count between first span of at least 6 days with TG > 5 ℃ and first span after July 1 (January 1 in SH) of 6 days with TG < 5 ℃	days
WSDI	Warm spell duration indicator	Annual count of days with at least 6 consecutive days when TX > 90th percentile	days
CSDI	Cold spell duration indicator	Annual count of days with at least 6 consecutive days when TN < 10th percentile	days
Temperature Frequency			
Tn10p	Cool nights	Percentage of days when TN < 10th percentile	days
Tx10p	Cool days	Percentage of days when TX < 10th percentile	days
Tn90p	Warm nights	Percentage of days when TN > 90th percentile	days
Tx90p	Warm days	Percentage of days when TX > 90th percentile	days
FD0	Frost days	Annual count when TN (daily minimum) < 0 ℃	days
SU25	Summer days	Annual count when TX (daily maximum) > 25 ℃	days
ID0	Ice days	Annual count when TX (daily maximum) < 0 ℃	days
TR20	Tropical nights	Annual count when TN (daily minimum) > 20 ℃	days
Precipitation			
Rx1day	Max 1-day precipitation amount	Monthly maximum consecutive 1-day precipitation	mm
Rx5day	Max 5-day precipitation amount	Monthly maximum consecutive 5-day precipitation	mm
SDII	Simple daily intensity index	Annual total precipitation divided by the number of wet days (defined as PRCP > = 1.0 mm) in the year	mm/day
R95p	Very wet days precipitation	Annual total PRCP when RR > 95th percentile	mm
R99p	Extremely wet days precipitation	Annual total PRCP when RR > 99th percentile	mm
PRCPTOT	Annual total wet-day precipitation	Annual total PRCP in wet days (RR > =1 mm)	mm
Precipitation Duration			
CDD	Consecutive dry days	Maximum number of consecutive days with RR < 1 mm	days
CWD	Consecutive wet days	Maximum number of consecutive days with RR > =1 mm	days
Precipitation Frequency			
R10	Number of heavy precipitation days	Annual count of days when PRCP > =10 mm	days
R20	Number of very heavy precipitation days	Annual count of days when PRCP > =20 mm	days

which can explicitly simulate the long-term spatial trajectories of multiple land use and land cover change (LUCCs), considering both human influences and climate effects. In addition, it was proved that the simulation of this model is effective for the future LUCC simulation under variously designed scenarios (Liu et al., 2017). Furthermore, this data shows strong potential to radically reduce uncertainty in global environmental modeling with finer resolution (Li et al., 2017).

3.1.3. Remote sensing data

Compared with the available Normalized Difference Vegetation Index (NDVI) datasets, such as SPOT-VGT-based NDVI, TM-based NDVI, AVHRR-based NDVI and MODIS-based NDVI (Yin et al., 2012), AVHRR-based NDVI was the best one to monitor vegetation change in this study, as it has the longest record of vegetation information. The latest version, 3 g. v1, spans the period July 1981 to December 2015 (https://ecocast.arc.nasa.gov/data/pub/gimms/) and is termed NDVI3g (third generation GIMMS NDVI from AVHRR sensors). Based on the data, vegetation changes and their response to climate changes, in global and regional scales, have been widely analyzed (Li et al., 2018b).

3.2. Methods

3.2.1. Maximum value composite

A Maximum Value Composite (MVC) was deployed. This is one of the most popular algorithms to composite time series of NDVI in multi-temporal scales, (such as daily, weekly, monthly or annually), and is commonly used to analyze variations in vegetation (Zhou et al., 2013; Li et al., 2018a). Specifically, at the pixel-by-pixel level, each NDVI value is achieved by choosing the highest pixel value from multi-temporal data. This results in the MVC image (Holben, 1986).

3.2.2. Trend analysis

Trend of NDVI at pixel scale can be estimated by ordinary least squares (Hou et al., 2015). A piece of code in MATLAB was used to calculate the trend of NDVI from 1982 to 2014. The formula (Gao et al., 2017; Jiapaer et al., 2015) is shown as below:

$$Slope = \frac{n \times \sum_{i=1}^{n} i \times NDVI_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} NDVI_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2} \quad (1)$$

where, n is the number of monitoring years (equal to 33 in this study), i denotes the year (=1, 2, 3,…, 33), $NDVI_i$ is the annual mean NDVI value in the ith year. When $Slope < 0$ means there is a decreasing trend in NDVI and vice versa.

3.2.3. Mann-Kendall test

The Mann-Kendall test (MK) is a non-distribution test, was developed by Mann (1945) and Kendall (1962). This method is widely employed to detect monotonic trends in series of environmental data as the required data is not in any particular order and not affected by outliers compared with other analysis methods. The original hypothesis H_0 is that the time series data, (x_1, x_2, x_3, …, x_n), are n independent, random variables with the distribution of the sample; in an alternative hypothesis, H_1, is bilateral inspection, for all $k, j \le n$, and $k \neq j$, the distribution of x_h and x_j is different, and statistic variable S is given by

$$S = \Sigma_{k=1}^{n-1} \Sigma_{j=k+1}^{n} Sgn(X_j - X_h) \quad (2)$$

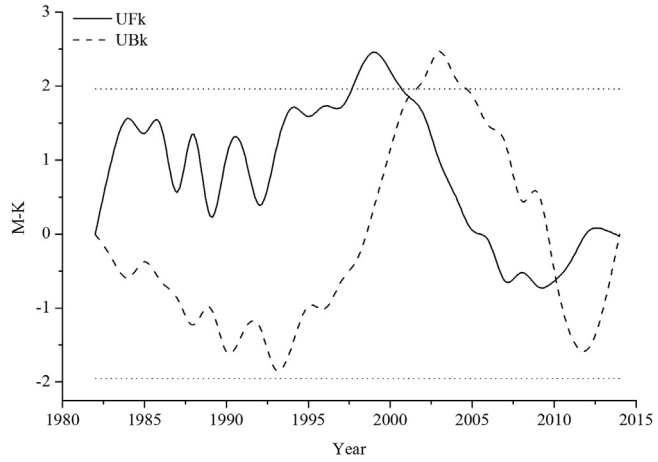

Fig. 2. Change trend and abrupt of average annual maximum NDVI in MP based on MK.

$$Sgn(X_j - X_h) = \begin{Bmatrix} +1 & if & (X_j - X_h) > 0 \\ 0 & if & (X_j - X_h) = 0 \\ -1 & if & (X_j - X_h) < 0 \end{Bmatrix} \tag{3}$$

$$Var(S) = \frac{1}{18}[n(n-1)(2n+5)] \tag{4}$$

When the sample size $n > 10$, the standard normal variable Z is computed using formula (5):

$$Z = \begin{Bmatrix} \frac{S-1}{\sqrt{Var(S)}} & if & S > 0 \\ 0 & if & S = 0 \\ \frac{S+1}{\sqrt{Var(S)}} & if & S < 0 \end{Bmatrix} \tag{5}$$

The value Z is the trend of NDVI here, when it is positive indicating an increasing trend during the study period, and vice versa. When $|Z| > Z_\alpha$ ($Z_{0.05} = 1.96$), the original hypothesis is unacceptable, indicating there is a up or down trend and significant at the α confidence level.

When the Mann-Kendall test is used to test the sequence mutation, the test statistic is different from that of the Z, by constructing a rank sequence (Li and Sun, 2015):

$$S_k = \sum_{i=1}^{k} \sum_{j}^{j-1} \partial_{ij} (k = 1, 2, \ldots n) \tag{6}$$

which,

$$\partial_{ij} = \begin{Bmatrix} 1 & x_i > x_j \\ 0 & x_i \leqslant x_j \end{Bmatrix} 1 \leqslant j \leqslant i \tag{7}$$

Defining statistical variables:

$$UF_k = \frac{[S_k - E(S_k)]}{\sqrt{Var(S_k)}} (k = 1, 2, \ldots n) \tag{8}$$

When

$$E(S_k) = k(k+1)/4 \tag{9}$$

$$Var(S_k) = k(k-1)(2k+5)/72 \tag{10}$$

UF_k is a standard normal distribution, given the level of significance α, if $|Uf| > U_{\partial/2}$, it shows that the sequence has obvious trend change.

$$\begin{cases} UB_k = -UF_k \\ k = n + 1 - k \end{cases} (k = 1, 2, \ldots n) \tag{11}$$

Through UF_k and UB_k, X trend and mutation time can be obtained. If $UF_k > 0$ (< 0), the sequence is on the rise (down) trend, when it exceeds the critical line, it indicates the rise or fall of the trend is significant. During the critical line, if UF_k and UB_k have intersection points, that intersection point is the beginning of the abrupt.

3.2.4. Correlation analysis

Pearson correlation, used for correlation analysis, is the most used measure of correlation and it is denoted as r, ranging between −1 and +1 and quantifies the direction and strength of the linear association between the two variables (Li et al., 2018a). The correlation between two variables can be positive or negative. The sign of the correlation coefficient represents the direction of the association. The magnitude of the correlation coefficient implies the strength of the association. (http://sphweb.bumc.bu.edu/otlt/mph-modules/bs/bs704_multivariable/bs704_multivariable5.html). Correlation between sets of data is a measure of how well they are related. In this study, correlation between vegetation and climate extremes are obtained to find out which are the main impact factors influencing the growth of vegetation.

4. Results and discussions

4.1. NDVI changes

4.1.1. Temporal change of NDVI in annual scale

Based on the results of the sequential Mann-Kendall test (MK) analysis, the change of average annual maximum NDVI in MP appear at two abrupt points at 2002 (significant at 0.05) and 2010 (non-significant) (Fig. 2), which divided the change into three periods: phase I (1982–2002), phase II (2003–2010), phase III (2011–2014). The result agrees with the previous finding (Miao et al., 2015).

From 2006, UF_k began to show below 0, indicating NDVI had started to turn into degradation. It is reported that in 2006 livestock represented the largest reported number of animals since 1924 in Mongolia based on census of 2006 (Angerer et al., 2008). The increase in livestock numbers matched well with the decline of NDVI, indicating that during this period the number of livestock can result in the change of NDVI.

Data in Fig. 3 shows the temporal change trend of average annual maximum NDVI in IM, M and MP in the three phases based on the Fig. 2. In phase I, average annual maximum NDVI showed non-significant increasing trends in IM, M and MP, with the 0.00035 $year^{-1}$, 0.00040 $year^{-1}$ and 0.00042 $year^{-1}$, respectively, indicating from 1982 to 2002, vegetation in MP improved non-significantly, while the speed of improvement in M is faster than that in IM. In phase II, average annual maximum NDVI also indicated upward trends in IM (Slope = 0.00107, r = 0.66), M (Slope = 0.00098, r = 0.58) and MP (Slope = 0.00103, r = 0.69). The change of trends in IM and MP were

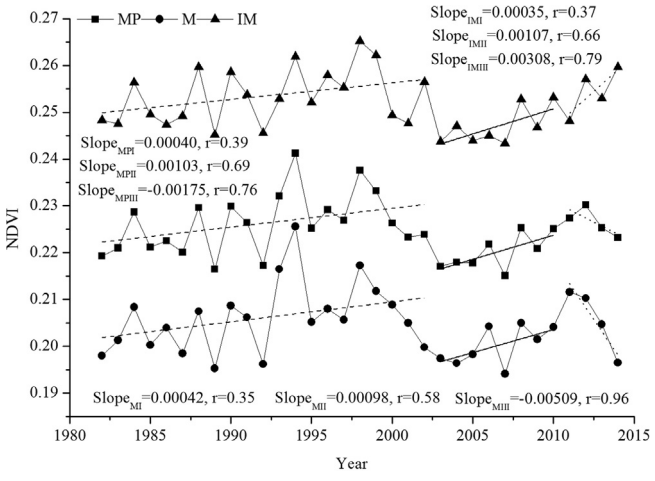

Fig. 3. Change of average annual maximum NDVI in IM, M and MP.

significant at 0.05. In phase III, NDVI in M and MP showed decreasing trends, while in IM it continued to increase.

These results indicated the projects implemented in IM, such as "Three-north Shelterbelt Project", "Grain for Green Project", "Beijing-Tianjin Sand Source Control Program", "Natural Forest Conservation Program" (Liu et al., 2011; Li et al., 2018b), began to work, which can protect and improve the ecological environment by increasing NDVI. Most projects began in 2002, which is why the increasing trend of vegetation in IM is higher than that of M in phase II. It is easy to understand that after 2010, the vegetation in IM continued increasing since the projects have continued. It is a reasonable assumption that vegetation changes in M which occurred without implementing such projects during the same time, had mainly been affected by natural factors. Bao et al (2016) also pointed out that M is an ideal natural area due to minimal human impacts on its ecosystem. Thus, it can be assumed that the vegetation increase shown from 1982 to 2010, and the subsequent decrease was mainly due to natural factors. In a similar location, IM had human activities such as protection projects and the vegetation continued to increase after 2010. Thus, human activities have an apparent effect on vegetation change and some of the related protection projects implemented in China are environmentally friendly.

Fig. 3 also shows that the average annual maximum NDVI in MP is more than 0.19, but NDVI in IM (0.24–0.27) was higher than that of in M (0.19–0.23), indicating that the vegetation in IM had higher coverage than that in M. That's mostly due to the large area of Gobi Desert located in the southern part of M, while there is a large area of forest in the north-eastern of IM (Miao et al., 2015).

4.1.2. Spatial change of yearly maximum NDVI

The results in Fig. 4 show the spatial change trend of average yearly maximum NDVI in MP by trend analysis and MK significant test about the period-by-pixel between NDVI and time series on the yearly scale.

Based on the change trend of NDVI in Fig. 4, it is seen that in MP 52.76% of the total area had NDVI decreasing (17.67% passed the MK test) in the recent 33 years, which was still larger than the NDVI-increased area (only 13.85% passed the MK test). This suggests that during the past 33 years, the vegetation in some parts of MP has suffered some degree of degradation. Areas with significant decreases were concentrated in the south-west and north-east of MP, while the areas where significantly increases are seen were scattered in the middle and north areas and concentrated in the south area of MP, especially in the southern part of IM, where there are some agricultural and pastoral zones. Sun et al. (2010) found that the significant increase in vegetation in this area was due to the newly implemented strategies and projects.

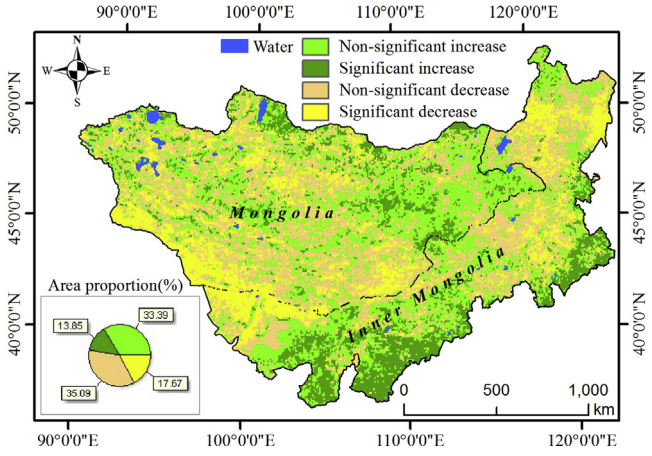

Fig. 4. Spatial pattern of change trend of yearly maximum NDVI in MP.

4.2. Influences of extreme climate indices

To discover the main extreme climate indicators affecting vegetation, relations between vegetation and extreme climate indices on the annual basis were obtained through Pearson correlation coefficient. The results are listed in the Table 2.

4.2.1. Influence of temperature-indices

Temperature is one of the main factors influencing vegetation growth, particularly temperature extremes which fall below or above specific thresholds at critical times during development (Hatfield and Prueger, 2015). These can significantly impact the growth of vegetation. Figuring out the causal impact factors among temperature extremes is the key step for temperature extremes adaptation options of vegetation. Table 2 showed that vegetation has a negative relation with intensity and duration of extreme temperature indices, except DTR, and with TXn, TNn, TNx and GSL significant at the 0.01 level. While vegetation has a positive relation with the frequency of extreme temperature indices, such as Tx10p, Tx90p, Tn90p, FD0 and ID0, but only with FD0 and ID0 significant at the 0.01 level and have a negative relation with TR20 ($p < 0.01$), Tn10p and SU25.

On an annual basis the intensity and duration of extreme low temperature are the main factors affecting vegetation growth in MP, compared with that of extreme high temperature. Consistent with the results of Hatfield et al. (2011) and Hatfield and Prueger (2015), who believed that changes of extreme low temperature have a more significant effect on growth and phenology, while extreme high temperature showed relatively less impact on plant growth as temperatures do not easily exceed the optimum due to the long and cold winters in most parts of MP (Zhang et al., 2012). Vegetation has a closer relationship with extreme warm night temperature. Hatfield and Prueger (2015) also proved that plant respiration rates were seriously affected by extreme high temperature at night, which can potentially reduced the ability of plant production.

The GSL has a negative effect on NDVI, indicating that longer GSL damages vegetation growth in MP, supporting previous research (Lindner et al., 2010). Lindner et al. (2010) found the longer GSL, particularly under the higher temperatures, benefits fungal diseases, which are bad for vegetation growth. Though many vegetation species have adapted to some severe environmental conditions by themselves (Lindner et al., 2010). However, they continue to be exposed to climate extremes, which may also impair their growth. Overall, the vegetation in MP has a significant and positive relation with FD0 and ID0. This is due to more days of FD0 and ID0, when less insect pests and diseases survive in the extreme cold weather (Chen and Li, 2009), thus, the vegetation can grow with less damage from pests.

4.2.2. Changes due to precipitation-indices

Precipitation is another key factor for the growth of vegetation, especially for the annual plants in the dry-dominated area (Reyer et al., 2013). Its effects are complex. For example, in the grassland areas in the arid regions, the evaporation rate can be exacerbated, which may result in water-shortages for the vegetation and hence inhibit its growth. Drought, a typical phenomenon, can lead to dominant grass species decreasing, and result in undesirable shrubs or alien weeds increasing by replacing the desirable grass species (Zhang, 1994). For example, in Ordos Plateau, *Stipa and Cynachum spp*. (shallow roots and depending on light rain events) have been replaced by *Artemisia spp* (deeper roots and depending on larger rain events) to adapt to the occasional drought (Cheng et al., 2007). Similarly, if precipitation extremes occur in the forest area, where precipitation is not the main limiting factor for vegetation growth (Hayhoe et al., 2007), the filtration ability of soil is rather weak due to rainfall events of high-intensity, frequency or long-duration. Vegetation growth may suffer from rushing away or root-hypoxia due to high soil moisture contents (Reyer et al., 2013).

In addition, from Table 2, it can be seen that vegetation has a

Table 2
Relations between extreme climatic indices and vegetation on the annual basis.

Types									
Extreme Temperature Indices	Intensity	TXn	TXx	TNn	TNx	DTR			
		−0.52**	−0.05	−0.54**	−0.34**	0.18			
	Duration	GSL	CSDI	WSDI					
		−0.56**	−0.20	−0.22					
	Frequency	Tx10p	Tx90p	Tn10p	Tn90p	FD0	ID0	SU25	TR20
		0.07	0.29	−0.06	0.17	0.42**	0.54**	−0.32	−0.53**
Extreme Precipitation Indices	Intensity	Rx1day	Rx5day	SDII	R95p	R99p	PRCPTOT		
		0.75**	0.81**	0.64**	0.83**	0.84**	0.86**		
	Duration	CWD	CDD						
		0.90**	−0.81**						
	Frequency	R10	R20						
		0.82**	0.76**						

Note: ** and * represent $p < 0.01$ and $p < 0.05$, respectively.

positive significant ($P < 0.01$) relation with extreme precipitation indices. It indicates that wetness precipitation extremes contribute to the growth of current vegetation in MP, while dry precipitation extremes have an adverse effect on the growth of current vegetation.

4.3. Potential effects analysis in the future

4.3.1. Simulation vegetation changes in the future

The simulation of future vegetation changes is an important procedure since it can provide crucial information, which can statistically support the study of the impacts of climate extremes on vegetation by foreseeing various possible future adverse conditions. Based on the LUCCs data, different kinds of land use and land cover in 2050 and 2100 were simulated (Fig. 5).

Under Scenario A and B series, the water areas remain the same and account for 0.5% of the total area (Table 3) with spatial distribution in the northern area of MP. Under Scenario B1 series, the aggregate forest area undergoes a much greater percentage increase trend than that of the Scenario A1 series, and in 2100, under all Scenarios A1 and B1 series it accounts for its highest proportion at 12.4% and 13.1%, respectively. Larger forest areas were mainly distributed in the north-east in IM, specifically in the Greater Khingan Mountains, while small areas are located in the northern area of M. It should be noted that under Scenario A2 series, forest area decreases sharply in MP, not only in IM, but also in M. The percentages of grassland area increase markedly under the Scenario A series and B2 series. In comparison, Scenario B1 series project decreasing percentage of grassland area. Farmland areas decrease in same rate under Scenario A1 and B1 series, whilst they increase in Scenario A2 and B2 series. The farmland is mainly distributed either side of the forest area in MP, particularly, in the north-east of IM. It can be seen that the farmland area in IM is larger than that of in M. For urban areas, their proportion show increasing trends under Scenario A2 series, while in the other three Scenarios they all remain in balance. Barren areas show decreased trends in all Scenarios.

4.3.2. Potential effects in the future

Today's climate extreme cases may be tomorrow's 'normal' events. Tomorrow's climate extremes may, therefore, present many new challenges (Norringtondavies, 2012). Thus, analyzing the existing effects of climate change are not enough. Their potential effects in the future should be better investigated, especially among pastoral and nomad communities (Ayal et al 2018), since these groups will suffer more from the impacts of climate extremes.

Compared with 2010, with greenhouse gases (GHGs) emissions decreasing, the proportion of V1 (including forest and grassland) and V2 (including V1 and farmland) will visibly increase (Table 3), especially under Scenario A1B, which already accounts for 83.4% and 84.0%, respectively. It indicates that vegetation changes in MP are also connected with future GHG emission. This result is consistent with findings from previous studies, which have shown that different levels of CO_2 can affect the composition of pastures by altering the species competition dynamics (Rojas-Downing et al., 2017).

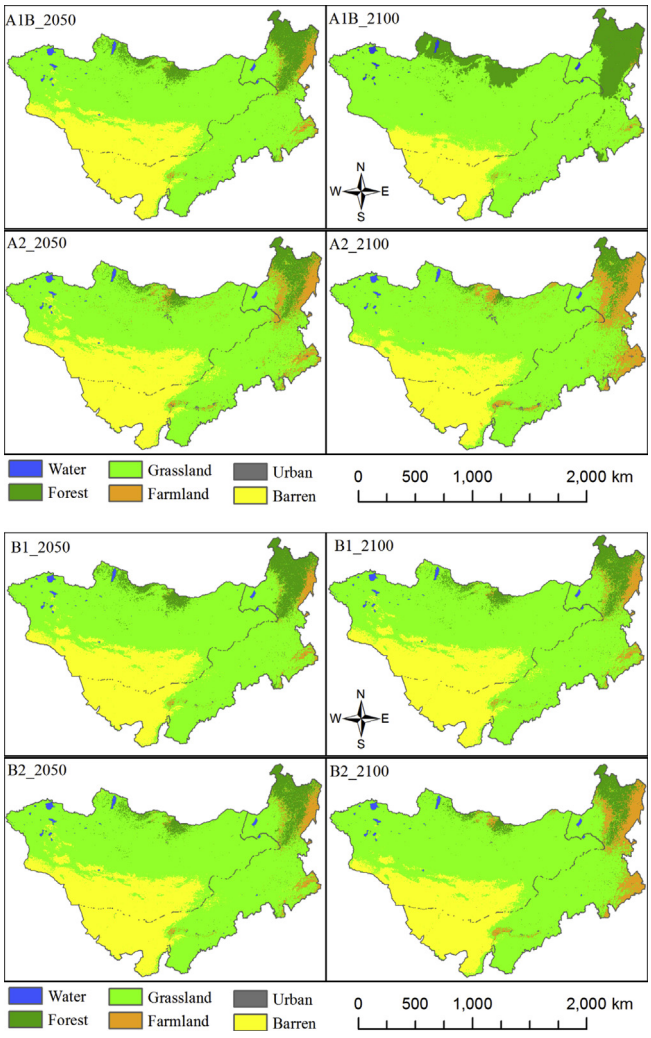

Fig. 5. The simulated land use and land cover in 2050 and 2100 under Scenario A1B, A2, B1 and B2.

Some researchers found that exposure to temperature variability will affect plants differently; because of their unique temperature responses. It is very likely that there will be more frequent hot and fewer cold temperature extremes over most land areas on daily and seasonal timescales, as the global mean surface temperature increases.

Table 3
The proportion of area in different land-use and land-cover in 2010, 2050 and 2100.

Land-use	2010	A1B_2050	A1B_2100	A2_2050	A2_2100	B1_2050	B1_2100	B2_2050	B2_2100
Water	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
Forest	0.050	0.066	0.124	0.047	0.031	0.070	0.131	0.053	0.043
Grassland	0.616	0.647	0.711	0.618	0.654	0.650	0.641	0.646	0.661
Farmland	0.050	0.026	0.006	0.056	0.088	0.021	0.001	0.031	0.060
Urban	0.001	0.002	0.002	0.005	0.006	0.002	0.002	0.002	0.002
Barren	0.277	0.253	0.153	0.269	0.216	0.251	0.219	0.262	0.229
Land-cover	2010	A1B_2050	A1B_2100	A2_2050	A2_2100	B1_2050	B1_2100	B2_2050	B2_2100
V1	0.666	0.713	0.834	0.665	0.685	0.721	0.772	0.700	0.704
V2	0.717	0.739	0.840	0.721	0.773	0.742	0.773	0.731	0.764

Note: proportion of V1 area is the sum of proportion areas of forest, grassland. While proportion of V2 area is the sum of proportion areas of V1 and farmland.

Furthermore, heat waves may occur with higher frequency and longer duration while occasional cold winter extremes may continue to occur. Increasing global mean surface temperature may also result in extreme precipitation events becoming more intense and frequent over most mid-latitude land masses and over wet tropical regions (IPCC, 2014).

Chronic periods of time exposure to climate extremes are expected to create a larger vulnerability of vegetation. Some vegetation will become weaker or even die, thereby reducing the species diversity and vegetation cover (Chen et al., 2014), while some vegetation will change its structure itself (Grimm et al., 2013) or develop some physiological mechanisms (Jones et al., 2012) to adapt to the extreme environment. Summarizing the potential effects of climate extremes on vegetation in MP is important due to its financial impact regarding livestock production which live on vegetation. This is a major source of wealth and well-being in MP.

4.4. Climate extremes adaptation and mitigation options of vegetation

4.4.1. Adaptation options

Based on the above results, it is important to consider potential climate extremes-induced shifts in local vegetation conditions and to develop management actions to minimize the unwanted effects of climate extremes. M and IM had experienced quite different political and economic conditions, vegetation dynamics and climate variations (Miao et al., 2013). The local knowledge and perceptions of ecosystem conditions, and consumption of resources are also different (Zhen et al., 2010). Consequently, they have different local institutions and have implemented different rural livelihood adaptations options to climate change (Wang et al., 2013).

The results in Table 3 show that farmland accounts for a large area in MP, especially in the north-eastern of IM. Because farmland is human-dominated area, it has the potential to contribute significantly to climate change adaptation through people's intervention, such as by improving cropping practices or a greater numbers of trees on farms (Mbow et al., 2014), changing crops and crop varieties, adjusting planting and harvest dates (Walthall et al., 2013). Animal husbandry in IM has changed from nomadic to settled in recent years, with nomads starting planting and farming. It seems the biggest problem in IM is to cope with the adverse influences of climate extremes, thus, large areas of farmland in IM should be more carefully cultivated, by choosing special crops or plants with roots which are drought and flood tolerant, since waterlogged or poorly drained soils can become anaerobic (Reyer et al., 2013). Assessments of irrigation thresholds under different projected scenarios in IM may help in long-range planning for water resource allocation, since agriculture is one of the primary water users (Hatfield et al., 2011).

Long time requirements for genetic selection (Hatfield et al., 2011) should be considered when taking adaptation options. The temporal variation in resource availability as induced by climate extremes, may reduce the effects of competition, allowing more species to coexist (Reyer et al., 2013). It may be assumed that many areas classified as unsuitable habitats for some kinds of vegetation under the current environment may become suitable due to climate extremes. A balanced understanding of the consequences of adaptation options and genetic responses to climate extremes will form the basis for more resilient grassland systems to climate extremes. Finding potential vulnerability areas of vegetation is vital for their future environment adaptation. In this research, based on the boundaries of grassland and forest in different scenarios in the year of 2050 and 2100, it is easy to see the transition zone of grassland and forest (Fig. 6). These areas not only indicated as a sensitive area in the model simulation, but also show the vegetation vulnerability areas in MP. No matter what scenario is in the future, the results may be included in the Fig. 6. Thus, in order to adapt to the future scenarios, focus should be paid on these potential vegetation vulnerability areas. In the I and II regions, both grassland and forest show vulnerability; planting forest-grassland vegetation should be fully considered in M, while in IM it should consider agroforestry due to a lot of farmland distributed outside it (see in Fig. 5). Moreover, agroforestry is seen as having the highest potential for carbon sequestration (above and below ground), which is also an ecologically based

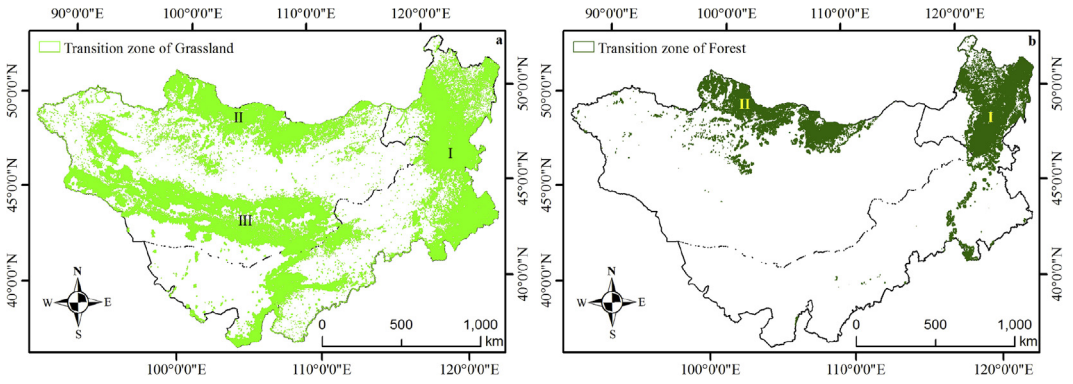

Fig. 6. Transition zone of Grassland and Forest.

traditional farming practice which integrates trees into the farming systems to increase agricultural productivity and ameliorate soil fertility, control erosion and conserve biodiversity (Bishaw et al., 2013). While in the III, drought and desertification-resistant grasses need to be considered both in M and IM. In addition, when grazing, especially in M due to its traditional nomadism, the vulnerable areas should be avoided. Preference should be given to the middle areas, which are stable, since under the different scenarios grasses grow rather well there. To make full use of resource endowment, grazing around the lake is also an option for nomadic herdsmen in M, especially during climate extremes due to the large area of lakes located in its north-west areas (Fig. 5) which also avoid the vulnerable vegetation areas.

It is worth noticing that large areas of Barren areas in MP (Fig. 5) are the primary source of sandstorms in Asia. Reducing or controlling the expansion of barren land requires international cooperation between M and IM, and government officials (policies), scientists (technologies) and local herdsmen (who have grazing experience and are familiar with the local environment) which should be initiated immediately. The integration of adaption options into the relevant policies is also required.

4.4.2. Mitigation options

More than half of Asian people live in rural areas, with many being pastoralists dependent on livestock and rangelands for their livelihood. Rangelands occupy over 4.3 billion acres (1.72 billion ha) on the Asian continent, almost 38% of the total land area (Angerer et al., 2008). Grasslands play a significant role in biogeochemical cycles and supply an ecosystem service for humans (He et al., 2015). Not only because it provides large sources for livestock, but also as it offers considerable potential for mitigation measures (Koslowski et al., 2012). Thus, the reliable detection and attribution of potential changes in vegetation growth is a prerequisite for the development of strategies for the sustainable management of ecosystems (Piao et al., 2015).

Figuring out the botanic baseline, especially the background variability to which plants are adapted to, can provide managers with a better understanding of the condition of plants' growth and can also allow a more thorough early detection and rapid response by comparing the different scenarios simulations. Table 3 shows that Scenario A1B sees the greatest increase in aggregate grassland in MP during the period from 2010 to 2100. It can also indicate that Scenario A1B poses a huge risk to the other vegetation, but it can indicate Scenario A1B is the best condition when planting grass. While Scenario A2 witnesses a slow increase of grassland from 2010 to 2050, followed by an apparent increase thereafter. The area of grassland increases very quickly under Scenario B2 before 2050, and then the increase slows. Under Scenario B1, grassland area expands quickly until 2050, and then narrows slowly. As a whole, Scenarios A1B, A2 and B2 maintain increased amounts of grassland. Scenario B1 is quite different from the other scenarios, with obvious increases first and then a slow decrease seen in grassland area under these projected conditions. Overall, Scenario A series projects greater increases in the aggregate area of grassland than the Scenario B series. In general, Scenario 1 series witnesses smaller increases in the area of farmland than Scenario 2 series.

Addressing mitigation issues in MP requires discovering the drivers of GHG emission and tackling them. Grassland, under different scenarios dominates land use in MP. Thus, when considering the mitigation, GHG emission from grassland systems is the key target. Previous researchers found that GHG emitted from grassland systems are CO_2 and nitrous oxide (N_2O) from soils, which are strongly influenced by the grazing intensity (Zhang et al., 2010). In addition, the volume of emissions in grassland system also depend strongly on the feed intake and animal species (Zhang et al., 2010). For grassland systems to effectively decrease emissions, overgrazing must be reduced and eventually stopped in some regions where the land was degraded heavily, while at the same time, protection polices must be implemented immediately. High quality and low emission animal species should be considered, and the types of intake grass must be accounted for. Sheepfolds in IM are the net sources of CO_2, CH_4 and N_2O (Chen et al., 2011). For nomadic areas in M, monitoring the environment around sheepfold is more important; this can guide the nomads moving from one place to another within the tolerable range of the environment, leaving the disturbed areas to recover naturally. Settled animal husbandry in IM and the management of the sheepfold should be unified to reduce the emissions. Thus, scientifically management of the sheepfolds in MP, is another way of GHG emission reduction.

Overall, the mitigation options are almost all related to improved grassland systems and the reduction of the total number of livestock or the restoration of degraded lands. These options require land-management alternatives in land-based activities related to grassland.

5. Limitations of the study

Although the dataset derived from this study was determined acceptable, the mean of average annual maximum data means that a loss of variation detail in inter-annual change is observed. This, in turn, prevents the paper from assessing how vegetation responds to changes in climate extremes and human disturbance, a matter which should be investigated further. In addition, lag times between vegetation and climate extremes in MP have not been investigated in this research. Indeed, growth and succession rates of vegetation and species interactions are likely to change in the future (Halofsky et al., 2013), which might contribute to changes in findings by other studies. Potential vegetation vulnerable areas and their adaptation and mitigation options are based on the results predicted by the predecessors (Li et al., 2017), and there will inevitably be a lot of uncertainties. The limits and barriers to adaptation are based on some ecological and natural resources in MP, and complicated adaptation efforts because of different social and cultural backgrounds (Zhen et al., 2010) also add uncertainty to the adaptation process. Taking a detailed look at how climate extremes and human disturbance affect vegetation should consider both direct effects and indirect effects, but this research only focus on the direct effects. Despite these limitations, the results obtained in this study are robust enough, and help to better understand the potential influence of climate extremes on vegetation on the site. They may also provide a basis for further mitigation and adaptation efforts.

6. Conclusions

This paper investigated trends on vegetation changes in temporal and spatial scales and their effect factors analysis. Compared with previous studies, the novelty of this research lies in the following points: (1) it has considered vegetation changes in the past (1982–2014) and future (2010–2100). (2) it has considered possible adaptation and mitigation options separately based in M and IM.

The obtained results are promising and indicate that the change of average annual maximum NDVI in MP appeared at two abrupt points in 2002 (significant at 0.05) and 2010 (non-significant). The high numbers of livestock in 2006 may be one of the factors leading to a reduction in the vegetation in MP. From 1982 to 2010, vegetation in IM, M and MP showed an increase with different change rates, while after 2010, it began to decrease in M and MP, but in IM it continued increasing due to the friendly environmental work carried out by China, especially in the southern agricultural and pastoral zone of IM. Climate extremes in MP play an important role in vegetation growth. In the future, vegetation in MP is expected to recover and increase in the period 2050 and 2100 under Scenario A1B, A2, B1 and B2 based on the LUCCs data. The Scenario A1B offers the best conditions for vegetation growth in MP compared with other three scenarios. As far as adaptation options are concerned, greater care to planning the use of farmland and of water is needed. Furthermore, potential vegetation vulnerability areas of grassland and forest in the future are pointed out, which is the key protected areas and for the adaptation, in M, planting forest-

grassland vegetation in II, drought - desertification resistant grass types in III, while in IM, agroforestry should be considered in I. Government officials (policies), scientists (technologies) and local herdsmen (grazing experiences, familiar with the local environment) should co-operate with each other to reduce or control the expansion of barren areas and integrating adaptation options into relevant policies should also be taken full consideration. In terms of mitigation options, Scenario A1B offers suitable conditions for emission reductions in MP. Attention should be paid to the GHG emitted from grassland systems, independently from the high quality and low emission animal species. The types of intake grass also need to be considered. In addition, management of sheepfolds in MP is also an important way for reducing GHG emission. A better understanding of how climate extremes influence vegetation in MP may assist policy makers and other concerned stakeholders in their efforts towards developing proper measures for a more sustainable use of such an important resource.

Acknowledgments

This study was jointly supported by National Natural Science Foundation of People's Republic of China (grant No. 41671095, 51761135024 and 61631011) and the National Key Research and Development Program of People's Republic of China (grant No. 2017YFE0107400) and the Financial Fund Planning Project in Inner Mongolia (grant No. 2018-ZME-KJXT-14).

References

Angerer, J., Han, G.D., Fujisaki, I., Havstad, K., 2008. Climate change and ecosystems of Asia with emphasis on inner Mongolia and Mongolia. Rangelands 30, 46–51.

Arefi, I.H., Saffari, M., Moradi, R., 2017. Evaluating planting date and variety management strategies for adapting winter wheat to climate change impacts in arid regions. Int. J. Clim. Change Strategies Manage. 9, 846–863.

Ayal, D.A., Radeny, M., Desta, S., Gebru, G., 2018. Climate variability, perceptions of pastoralists and their adaptation strategies: implications for livestock system and diseases in Borana zone. Int. J. Clim. Change Strategies Manage. 10 (4), 596–615. https://doi.org/10.1108/IJCCSM-06-2017-0143.

Bao, G., Bao, Y.H., Sanjjava, A., Qin, Z.H., Zhou, Y., Xu, G., 2016. NDVI-indicated long-term vegetation dynamics in Mongolia and their response to climate change at biome scale. Int. J. Climatol. 35, 4293–4306.

Bishaw, B., Henry, N., Jeremias, M., Abdu, A., Jonathan, M., Gemedo, D., Tewodros, A., Kathleen, G., Habtemariam, K., Ian, K.D., Eike, L., Cheikh, M., 2013. In: Davis, Caryn M., Bernart, Bryan, Dmitriev, Aleksandra (Eds.), Farmers' Strategies for Adapting to and Mitigating Climate Variability and Change through Agroforestry in Ethiopia and Kenya. Forestry Communications Group, Oregon State University, Corvallis, Oregon.

Chen, S.H., Li, J.M., 2009. Meteorological conditions and prewarning of grasshopper plagues in Inner Mongolia. Meteorol Sci Technol 37 (1), 48–51.

Chen, W.W., Wolf, B., Brüggemann, N., Butterbach-Bahl, K., Zheng, X., 2011. Annual emissions of greenhouse gases from sheepfolds in Inner Mongolia. Plant Soil 340 (1–2), 291–301.

Chen, Y., Deng, H., Li, B., Li, Z., Xu, Z., 2014. Abrupt change of temperature and precipitation extremes in the arid region of northwest China. Quat. Int. 336, 35–43.

Cheng, X., An, S., Chen, J., Li, B., Liu, Y., Liu, S., 2007. Spatial relationships among species, above-ground biomass, N and P in degraded grassland in Ordos Plateau, northwest China. J. Arid Environ. 68 (4), 652–667.

Dan, S., Li, H.J., Ping, L.Y., De, X.E., 2013. Effects of climate change on vegetation in desert steppe Inner Mongolia. Nat. Resour. 4, 319–322.

Ferńandez-Gimenez, M.E., Batkhishig, B., Batbuyan, B., 2012. Cross-boundary and cross-level dynamics increase vulnerability to severe winter disasters (dzud) in Mongolia. Global Environ. Change 22, 836–851.

Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.K., Allen, S.K., Tignor, M., Midgley, P.M., 2012. Managing the risks of extreme events and disasters to advance climate change adaptation. In: A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 582.

Gao, J.B., Jiao, K.W., Wu, S.H., Ma, D.Y., Zhao, D.S., Yin, Y.H., Dai, E.F., 2017. Past and future influence of climate change on spatially heterogeneous vegetation activity in China. Earths Future 1–20.

Grimm, N.B., Chapin, F.S., Bierwagen, B., Gonzalez, P., Groffman, P.M., Luo, Y.Q., Melton, F., Nadelhoffer, K., Pairis, A., Raymond, P.A., Schimel, J., Williamson, C.E., 2013. The impacts of climate change on ecosystem structure and function. Front. Ecol. Environ. 11, 474–482.

Hayhoe, K., Wak,e, C., Huntington, T., Luo, L., Schwartz, M., Sheffield, J., Wood, E., Anderson, B., Bradbury, J., Degaetano, A., Troy, T., Wolfe, D., 2007. Past and future changes in climate and hydrological indicators in the US Northeast. Clim. Dynam. 28, 381–407.

He, C.Y., Tian, J., Gao, B., Zhao, Y.Y., 2015. Differentiating climate- and human-induces drivers of grassland degradation in the Liao River Basin, China. Environ. Monit. Assess. 187, 4199.

Hatfield, J.L., Boote, K.J., Kimball, B.A., Ziska, L.H., Izaurralde, R.C., Ort, D., Thomson, A.M., Wolfe, D.W., 2011. Climate impacts on agriculture: implications for crop production. Agron. J. 103, 351–370.

Hatfield, J.L., Prueger, J.H., 2015. Temperature extremes: effect on plant growth and development. Weather Clim. Extremes 10, 4–10.

Halofsky, J.E., Hemstrom, M.A., Conklin, D.R., Halofsky, J.S., Kerns, B.K., Bachelet, D.B., 2013. Assessing potential climate change effects on vegetation using a linked model approach. Ecol. Model. 266, 131–143.

Hoover, D.L., Knapp, A.K., Smith, M.D., 2016. The immediate and prolonged effects of climate extremes on soil respiration in a mesic grassland. J. Geophys. Res. Biogeosci. 121, 1034–1044.

Hou, W.J., Gao, J.B., Wu, S.H., Dai, E.F., 2015. Interannual variations in growing-season NDVI and its correlation with climate variables in the southwestern karst region of China. Rem. Sens. 7, 11105–11124.

Holben, B., 1986. Characteristics of maximum-value composite images from temporal AVHRR data. Int. J. Remote Sens. 7, 1417–1434.

IPCC, 2014. In: Core Writing Team, Pachauri, R.K., Meyer, L.A. (Eds.), Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland.

Jiapaer, G.L., Liang, S.L., Yi, Q.X., Liu, J.P., 2015. Vegetation dynamics and responses to recent climate change in Xinjiang using leaf area index as an indicator. Ecol. Ind. 58, 64–76.

Jones, J.A., Creed, I.F., Hatcher, K.L., 2012. Ecosystem processes and human influences regulate stream flow response to climate change at long-term ecological research sites. Bioscience 62, 390–404.

Kendall, M.G., 1962. Rank correlation methods. Hafner, New York, NY, USA.

Kharin, V.V., Zwiers, F.W., Zhang, X., Hegerl, G.C., 2013. Changes in temperature and precipitation extremes in the IPCC ensemble of global coupled model simulations. Clim. Change 119, 345–357.

Koslowski, F., Wilkes, A., Moran, D., 2012. Developing climate-smart livestock systems in Inner Mongolia, China. UK from Agricultural Economics Society. No 135111 In: 86th Annual Conference, April 16-18, 2012. Warwick University, Coventry, pp. 24.

Li, C.L., Wang, J., Hu, R.C., Yin, S., Bao, Y.H., Ayal, D.Y., 2018a. Relationship between vegetation change and extreme climate indices on the Inner Mongolian Plateau, China, from 1982 to 2013. Ecol. Ind. 89, 101–109.

Li, C.L., Walter, L.F., Yin, J., Hu, R.C., Wang, J., Yang, C.S., Yin, Shan, Bao, Y.H., Ayal, D.Y., 2018b. Assessing vegetation response to multi-time-scale drought across Inner Mongolian Plateau. J. Cleaner Prod. 179, 210–216.

Li, Z., Sun, D.Y., 2015. Trend and abrupt analysis of rainfall change during last 50 years in the Weihe Basin. Earth Sci. 4, 228–234.

Li, X., Chen, G.Z., Liu, X.P., Liang, X., Wang, S.J., Chen, Y.M., Pei, F.S., Xu, X.C., 2017. A new global land-use and land-cover change product at a 1-km resolution for 2010–2100 based on human-environment interactions. Ann. Am. Assoc. Geograph.

Lindner, M., Maroschek, M., Netherer, S., Kremer, A., Barbati, A., Garcia-Gonzalo, J., Seid, R., Delzon, S., Corona, P., Kolström, M., Lexer, J., Marchetti, M., 2010. Climate change impacts, adaptive capacity, and vulnerability of European forest ecosystems. For. Ecol. Manage. 259, 698–709.

Liu, X.P., Liang, X., Li, X., Xu, X.C., Ou, J.P., Chen, Y.M., Li, S.Y., Wang, S.J., Pei, F.S., 2017. A future land sue simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. Landscape Urban Plann. 168, 94–116.

Liu, Y.C., Wang, Q.F., Yu, G.R., Zhu, X.J., Zhan, X.Y., Guo, Q., Yang, H., Li, S.G., Hu, Z.M., 2011. Ecosystems carbon storage and carbon sequestration potential of two main tree species for the Grain for Green Project on China's hilly Loess Plateau. Acta Ecol. Sin. 31, 4277–4286.

Mann, H.B., 1945. Nonparametric tests against trend. Econometrica 13, 245–259.

Mbow, C., Smith, P., Skole, D., Duguma, L., Bustamante, M., 2014. Achieving mitigation and adaptation to climate change through sustainable agroforestry practices in Africa. Curr. Opin. Environ. Sustain. 6, 8–14.

Miao, L., Luan, Y., Luo, X., Liu, Q., Moore, J., Nath, R., He, B., Zhu, F., Cui, X., 2013. Analysis of the phenology in the Mongolian Plateau by inter-comparison of global vegetation datasets. Rem. Sens. 5, 5193–5208.

Miao, L.J., Liu, Q., Fraser, R.C., He Bin, Cui, X.F., 2015. Shifts in vegetation growth in response to multiple factors on the Mongolian Plateau from 1982-2011, Physics and Chemistry of the Earth, 87–88, 50–59.

Nicholls, S.I.N., Easterling, D., Goodess, C.M., Kanae, S., Kossin, J., Luo, Y., Marengo, J., McInnes, K., Rahimi, M., Reichstein, M., Sorteberg, A., Vera, C., Zhang, X., 2012. Changes in climate extremes and their impacts on the natural physical environment. In: Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.-K., Allen, S.K., Tignor, M., Midgley, P.M. (Eds.), Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 109–230 A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC).

Mu, S.J., Chen, Y.Z., Li, J.L., Ju, W.M., Odeh, I.O.A., Zou, X.L., 2013. Grassland dynamics in response to climate change and human activities in Inner Mongolia, China between 1985 and 2009. Rangeland J. 35, 315–329.

Norringtondavies, G., 2012. Managing climate extremes and disasters in the agricultural sector: lessons from the IPCC SREX report. Convergence Int. J. Res. New Media Technol. 5 (5/6), 271–285.

Piao, S.L., Yin, G.D., Tan, J.G., Cheng, L., Huang, M.T., Li, Y., Liu, R.G., Mao, J.F., Myneni, R.G., Peng, S.S., Poulter, B., Shi, X.Y., Xiao, Z.Q., Zeng, N., Zeng, Z.Z., Wang, Y.P.,

2015. Detection and attribution of vegetation greening trend in China over the last 30 years. Glob. Change Biol. 21, 1601.
Rao, M.P., Davi, N.K., Arrigo, R.D.D., Skees, J., Nachin, B., Leland, C., Lyon, B., Wang, S.Y., Bayambasuren, Q., 2015. Dzuds, drought, and livestock mortality in Mongolia. Environ. Res. Lett. 10, 074012.
Reyer, C., Leuzinger, S., Rammig, A., Wolf, A., Bartholomeus, R.P., Bonfante, A., Lorenzi, F.D., Dury, M., Gloning, P., Jaoudé, R.A., Klein, T., Kuster, T.M., Martins, M., Niedrist, G., Riccardi, M., Wohlfahrt, G., Angelis, P.D., Dato, G.D., François, L., Menzel Pereira, A., 2013. A plant's perspective of extremes: terrestrial plant responses to changing climatic variability. Glob. Change Biol. 19, 75–89.
Reynolds, J.F., Smith, D.M., Lambin, E.F., Turner, B.L., Mortimore, M., Batterbury, S.P., Downing, T.E., Dowlatabadi, H., Fernández, R.J., Herrick, J.E., Huber-Sannwald, E., Jiang, H., Leemans, R., Lynam, T., Maestre, F.T., Ayarza, M., Walker, B., 2007. Global desertification: building a science for dryland development. Science 316, 847–851.
Rojas-Downing, M.M., Nejadhashemi, A.P., Harrigan, T., Woznicki, S.A., 2017. Climate change and livestock: impacts, adaptation, and mitigation. Clim. Risk Manage. 16, 145–163.
Seneviratne, S.I., Nicholls, N., Easterling, D., Goodess, C.M., Kanae, S., Kossin, J., Luo, Y., Marengo, J., McInnes, K., Rahimi, M., Reichstein, M., Sorteberg, A., Vera, C., Zhang, X., 2012. Changes in climate extremes and their impacts on the natural physical environment. In: Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.-K., Allen, S.K., Tignor, M., Midgley, P.M. (Eds.), Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 109–230 A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC).
Sillmann, J., Kharin, V.V., Zhang, X., Zwiers, F.W., Bronaugh, D., 2013a. Climate extremes indices in the CMIP5 multimodel ensemble: Part 1. Model evaluation in the present climate. J. Geophys. Res. Atmos. 118, 1716–1733.
Sillmann, J., Kharin, V.V., Zwiers, F.W., Zhang, X., Bronaugh, D., 2013b. Climate extremes indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections. J. Geophys. Res. Atmos. 118, 2473–2493.
Sun, Y.L., Guo, P., Yan, X.D., Zhao, T.B., 2010. Dynamics of vegetation cover and its relationship with climate change and human activities in Inner Mongolia. J. Nat. Resour. 25, 407–414.
Tian, F., Herzschuh, U., Mischke, S., Schlütz, F., 2014. What drives the recent intensified vegetation degradation in Mongolia – Climate change or human activity? Holocene 24, 1206–1215.
Walthall, C.L., Hatfield, J., Backlund, P., Hauser, R., Lengnick, L., Marshall, E., Walsh. M., 2013. USDA Climate Change and U.S. Agriculture - An Assessment of Effects and Adaptation Responses. https://www.usda.gov/oce/climate_change/effects_2012/effects_agriculture.htm.
Wang, J., Brown, D.G., Agrawal, A., 2013. Climate adaptation, local institutions, and rural livelihoods: a comparative study of herder communities in Mongolia and Inner Mongolia, China. Glob. Environ. Change 23, 1673–1683.
Wu, J., Xu, Y., Gao, X.J., 2017. Projected changes in mean and extreme climates over Hindu Kush Himalayan region by 21 CMIP5 models. Adv. Clim. Chang. Res. 8, 176–184.
Xu, Y., Wu, J., Shi, Y., Zhou, B.T., Li, R.K., Wu, J., 2015. Changes in extreme climate events over China based on CMIP5. Atmos. Cceanic Sci. Lett. 8 (4), 185–192.
Yin, H., Udelhoven, T., Fensholt, R., Pflugmacher, D., Hostert, P., 2012. How Normalized Difference Vegetation Index (NDVI) Trends from Advanced Very High Resolution Radiometer (AVHRR), and Système Probatoire d'Observation de la Terre VEGETATION (SPOT VGT) time series differ in agricultural areas: an inner mongolian case study. Rem. Sens. 4, 3364–3389.
Zhang, F., Qi, J., Li, F.M., Li, C.S., Li, C.B., 2010. Quantifying nitrous oxide emissions from Chinese grasslands with a process-based model. Biogeosciences 7, 2039–2050.
Zhang, X.Y., Hu, Y.F., Zhuang, D.F., Qi, Y.Q., Ma, X., 2009. NDVI spatial pattern and its differentiation on the Mongolian Plateau. J. Geog. Sci. 19, 403–415.
Zhang, Q., Kong, D.D., Singh, V.P., Shi, P.J., 2017. Response of vegetation to different time-scales drought across China: spatiotemporal patterns, causes and implications. Global Planet. Change 152, 1–11.
Zhang, W., He, M.Y., Li, Y.H., Cui, Z.J., Wang, Z.L., Yu, Z., 2012. Quaternary glacier development and the relationship between the climate change and tectonic uplift in the Helan Mountains. Chin. Sci. Bull. 57, 4491–4504.
Zhang, X.S., 1994. The optimization pattern and principle of grassland construction and ecological background of Maowusu sandland. Acta Phytoecol. Sin. 18, 1–16.
Zhen, L., Ochirbat, B., Lv, Y., Wei, Y.J., Liu, X.L., Chen, J.Q., Yao, Z.J., Li, F., 2010. Comparing patterns of ecosystem service consumption and perceptions of range management between ethnic herders in Inner Mongolia and Mongolia. Environ. Res. Lett. 5, 15001–15011.
Zhou, Y., Chen, J., Chen, X.H., Cao, X., Zhu, X.L., 2013. Two important indicators with potential to identify Caragana microphylla in xilin gol grassland from temporal MODIS data. Ecol. Ind. 34, 520–527.